BIVE, VINCE EMMANUEL C.

COE005 – Prediction and Machine Learning **Homework 2 – Neural Style Transfer**

A. Chosen Base Photo

B. Chosen Art Styles

Ukiyo-e and Fernando Amorsolo

C. Code and Simulations

Step 1. Import the libraries needed for NST

```
import os
import tensorflow as tf
# Load compressed models from tensorflow_hub
os.environ['TFHUB_MODEL_LOAD_FORMAT'] = 'COMPRESSED'

import IPython.display as display

import matplotlib.pyplot as plt
import matplotlib as mpl
mpl.rcParams['figure.figsize'] = (12, 12)
mpl.rcParams['axes.grid'] = False

import numpy as np
import PIL.Image
import time
import functools
```

Define a function that will convert the produced image later.

```
def tensor_to_image(tensor):
  tensor = tensor*255
  tensor = np.array(tensor, dtype=np.uint8)
  if np.ndim(tensor)>3:
    assert tensor.shape[0] == 1
    tensor = tensor[0]
  return PIL.Image.fromarray(tensor)
```

Step 2. Gathering data. Import the base image and the style.

```
content = 'TIP_TechnoCore.jpg'
style1 = 'Ukiyo-e_Style.jpg'
```

Step 3. Data Preparation. Set the dimensions of the images to 512

```
def load_img(path_to_img):
  max_dim = 512
  img = tf.io.read_file(path_to_img)
  img = tf.image.decode_image(img, channels=3)
  img = tf.image.convert_image_dtype(img, tf.float32)

  shape = tf.cast(tf.shape(img)[:-1], tf.float32)
  long_dim = max(shape)
  scale = max_dim / long_dim

  new_shape = tf.cast(shape * scale, tf.int32)

  img = tf.image.resize(img, new_shape)
  img = img[tf.newaxis, :]
  return img

def imshow(image, title=None):
  if len(image.shape) > 3:
    image = tf.squeeze(image, axis=0)

  plt.imshow(image)
  if title:
    plt.title(title)

content_image = load_img(content)
style_image_1 = load_img(style1)

plt.subplot(1, 2, 1)
imshow(content_image, 'Content Image')

plt.subplot(1, 2, 2)
imshow(style_image_1, 'Style Image')
```

Step 4. Choose a model. For this simulation, VGG19 will be used.

```
x = tf.keras.applications.vgg19.preprocess_input(content_image*255)
x = tf.image.resize(x, (224, 224))
vgg = tf.keras.applications.VGG19(include_top=True, weights='imagenet')
prediction_probabilities = vgg(x)
prediction_probabilities.shape
```

```
Out[20]: TensorShape([1, 1000])
```

```
predicted_top_5 =
tf.keras.applications.vgg19.decode_predictions(prediction_probabilities.numpy())[0]
[(class_name, prob) for (number, class_name, prob) in predicted_top_5]
```

```
Out[21]: [('cinema', 0.29461548),
          ('library', 0.04050183),
          ('fire_engine', 0.039418697),
          ('planetarium', 0.03768365),
          ('freight_car', 0.03280036)]
```

Step 5: Show the layers of VGG19 and choose content and style layers from the given.

```
vgg = tf.keras.applications.VGG19(include_top=False, weights='imagenet')
print()
for layer in vgg.layers:
  print(layer.name)
```

```
input_4
block1_conv1
block1_conv2
block1_pool
block2_conv1
block2_conv2
block2_pool
block3_conv1
block3_conv2
block3_conv3
block3_conv4
block3_pool
block4_conv1
block4_conv2
block4_conv3
block4_conv4
block4_pool
block5_conv1
block5_conv2
block5_conv3
block5_conv4
block5_pool
```

Selected layers:

```
content_layers = ['block5_conv4']

style_layers_1 = ['block1_conv1',
                'block2_conv2',
                'block3_conv3',
                'block4_conv4',
                'block5_conv4']

num_content_layers = len(content_layers)
num_style_layers = len(style_layers_1)
```

Step 6. Create the model.

```
def vgg_layers(layer_names):
  """ Creates a VGG model that returns a list of intermediate output values."""
  # Load our model. Load pretrained VGG, trained on ImageNet data
  vgg = tf.keras.applications.VGG19(include_top=False, weights='imagenet')
  vgg.trainable = False

  outputs = [vgg.get_layer(name).output for name in layer_names]

  model = tf.keras.Model([vgg.input], outputs)
  return model

style_extractor = vgg_layers(style_layers_1)
style_outputs_1 = style_extractor(style_image_1*255)

for name, output in zip(style_layers_1, style_outputs_1):
  print(name)
  print("  shape: ", output.numpy().shape)
  print("  min: ", output.numpy().min())
  print("  max: ", output.numpy().max())
  print("  mean: ", output.numpy().mean())
  print()
```

```
block1_conv1
  shape:  (1, 344, 512, 64)
  min:  0.0
  max:  827.922
  mean:  37.736057

block2_conv2
  shape:  (1, 172, 256, 128)
  min:  0.0
  max:  6855.9336
  mean:  198.92072

block3_conv3
  shape:  (1, 86, 128, 256)
  min:  0.0
  max:  8773.462
  mean:  527.5477

block4_conv4
  shape:  (1, 43, 64, 512)
  min:  0.0
  max:  7374.769
  mean:  52.64414

block5_conv4
  shape:  (1, 21, 32, 512)
  min:  0.0
  max:  212.26912
  mean:  1.2772448
```

Step 7. Calculate the chosen style.

```
def gram_matrix(input_tensor):
  result = tf.linalg.einsum('bijc,bijd->bcd', input_tensor, input_tensor)
  input_shape = tf.shape(input_tensor)
  num_locations = tf.cast(input_shape[1]*input_shape[2], tf.float32)
  return result/(num_locations)
```

Extract the Ukiyo-e Style and the TIP TechnoCore image.

```
class StyleContentModel(tf.keras.models.Model):
  def __init__(self, style_layers_1, content_layers):
    super(StyleContentModel, self).__init__()
    self.vgg = vgg_layers(style_layers_1 + content_layers)
    self.style_layers_1 = style_layers_1
    self.content_layers = content_layers
    self.num_style_layers_1 = len(style_layers_1)
    self.vgg.trainable = False

  def call(self, inputs):
    "Expects float input in [0,1]"
    inputs = inputs*255.0
    preprocessed_input = tf.keras.applications.vgg19.preprocess_input(inputs)
    outputs = self.vgg(preprocessed_input)
    style_outputs_1, content_outputs = (outputs[:self.num_style_layers_1],
                                        outputs[self.num_style_layers_1:])

    style_outputs_1 = [gram_matrix(style_output)
                       for style_output in style_outputs_1]

    content_dict = {content_name: value
                    for content_name, value
                    in zip(self.content_layers, content_outputs)}

    style_dict = {style_name: value
                  for style_name, value
                  in zip(self.style_layers_1, style_outputs_1)}

    return {'content': content_dict, 'style_1': style_dict}

extractor = StyleContentModel(style_layers_1, content_layers)

results = extractor(tf.constant(content_image))

print('Styles:')
for name, output in sorted(results['style_1'].items()):
  print("  ", name)
  print("    shape: ", output.numpy().shape)
  print("    min: ", output.numpy().min())
```

```
  print("    max: ", output.numpy().max())
  print("    mean: ", output.numpy().mean())
  print()

print("Contents:")
for name, output in sorted(results['content'].items()):
  print("  ", name)
  print("    shape: ", output.numpy().shape)
  print("    min: ", output.numpy().min())
  print("    max: ", output.numpy().max())
  print("    mean: ", output.numpy().mean())
```

```
Styles:
   block1_conv1
    shape:  (1, 64, 64)
    min:  0.0043622456
    max:  18652.803
    mean:  720.94574

   block2_conv2
    shape:  (1, 128, 128)
    min:  0.10063007
    max:  289140.9
    mean:  15081.095

   block3_conv3
    shape:  (1, 256, 256)
    min:  1884.2374
    max:  1421697.9
    mean:  125352.05

   block4_conv4
    shape:  (1, 512, 512)
    min:  0.0
    max:  171586.17
    mean:  1847.2015

   block5_conv4
    shape:  (1, 512, 512)
    min:  0.0
    max:  860.8994
    mean:  0.66881514

Contents:
   block5_conv4
    shape:  (1, 24, 32, 512)
    min:  0.0
    max:  135.26706
    mean:  0.6293256
```

Step 8. Gradient Descent. Select the extracted content and style image.

```
style_targets_1 = extractor(style_image_1)['style_1']
content_targets = extractor(content_image)['content']
```

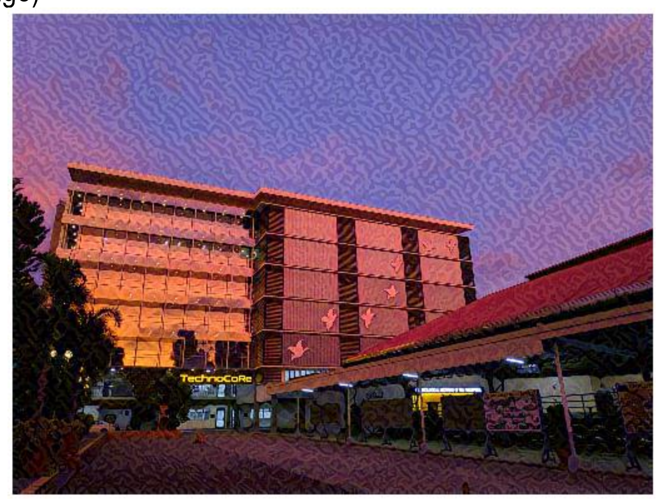
Optimize.

```
image = tf.Variable(content_image)

def clip_0_1(image):
  return tf.clip_by_value(image, clip_value_min=0.0, clip_value_max=1.0)

opt = tf.keras.optimizers.Adam(learning_rate=0.02, beta_1=0.99, epsilon=1e-1)

style_weight=1e-2
content_weight=1e4

def style_content_loss(outputs):
    style_outputs_1 = outputs['style_1']
    content_outputs = outputs['content']
    style_loss = tf.add_n([tf.reduce_mean((style_outputs_1[name]-style_targets_1[name])**2)
```

```
                         for name in style_outputs_1.keys()])
    style_loss *= style_weight / num_style_layers

    content_loss = tf.add_n([tf.reduce_mean((content_outputs[name]-content_targets[name])**2)
                          for name in content_outputs.keys()])
    content_loss *= content_weight / num_content_layers
    loss = style_loss + content_loss
    return loss
```

Update the image.

```
@tf.function()
def train_step(image):
  with tf.GradientTape() as tape:
    outputs = extractor(image)
    loss = style_content_loss(outputs)

  grad = tape.gradient(loss, image)
  opt.apply_gradients([(grad, image)])
  image.assign(clip_0_1(image))

train_step(image)
train_step(image)
train_step(image)
tensor_to_image(image)
```



Step 9. Perform the long optimization method

```
import time
start = time.time()

epochs = 10
steps_per_epoch = 10

step = 0
```

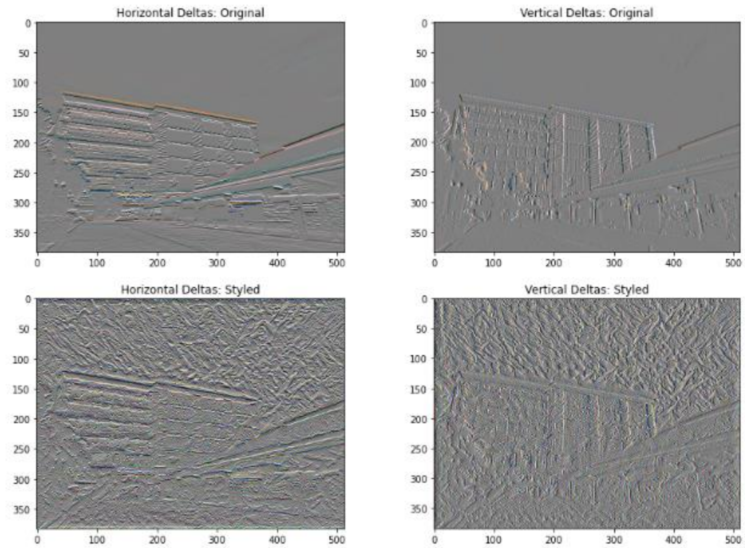
```
for n in range(epochs):
  for m in range(steps_per_epoch):
    step += 1
    train_step(image)
    print(".", end='', flush=True)
  display.clear_output(wait=True)
  display.display(tensor_to_image(image))
  print("Train step: {}".format(step))

end = time.time()
print("Total time: {:.1f}".format(end-start))
```

```
Train step: 100
Total time: 2946.8
```

Decrease the frequency.

```
def high_pass_x_y(image):
  x_var = image[:, :, 1:, :] - image[:, :, :-1, :]
  y_var = image[:, 1:, :, :] - image[:, :-1, :, :]

  return x_var, y_var

x_deltas, y_deltas = high_pass_x_y(content_image)

plt.figure(figsize=(14, 10))
plt.subplot(2, 2, 1)
imshow(clip_0_1(2*y_deltas+0.5), "Horizontal Deltas: Original")

plt.subplot(2, 2, 2)
imshow(clip_0_1(2*x_deltas+0.5), "Vertical Deltas: Original")

x_deltas, y_deltas = high_pass_x_y(image)
```

```
plt.subplot(2, 2, 3)
imshow(clip_0_1(2*y_deltas+0.5), "Horizontal Deltas: Styled")

plt.subplot(2, 2, 4)
imshow(clip_0_1(2*x_deltas+0.5), "Vertical Deltas: Styled")
```




```
def total_variation_loss(image):
  x_deltas, y_deltas = high_pass_x_y(image)
  return tf.reduce_sum(tf.abs(x_deltas)) + tf.reduce_sum(tf.abs(y_deltas))

total_variation_loss(image).numpy()
```

```
Out[64]: 151204.47
```

```
tf.image.total_variation(image).numpy()
```

```
Out[65]: array([151204.47], dtype=float32)
```

```
total_variation_weight=30

@tf.function()
def train_step(image):
  with tf.GradientTape() as tape:
    outputs = extractor(image)
    loss = style_content_loss(outputs)
    loss += total_variation_weight*tf.image.total_variation(image)

  grad = tape.gradient(loss, image)
  opt.apply_gradients([(grad, image)])
  image.assign(clip_0_1(image))
```

Step 10. Re-optimize the image.

```
opt = tf.keras.optimizers.Adam(learning_rate=0.02, beta_1=0.99, epsilon=1e-1)
image = tf.Variable(content_image)

import time
start = time.time()

epochs = 10
steps_per_epoch = 20

step = 0
for n in range(epochs):
  for m in range(steps_per_epoch):
    step += 1
    train_step(image)
    print(".", end='', flush=True)
  display.clear_output(wait=True)
  display.display(tensor_to_image(image))
  print("Train step: {}".format(step))

end = time.time()
print("Total time: {:.1f}".format(end-start))
```

```
Train step: 200
Total time: 6050.6
```

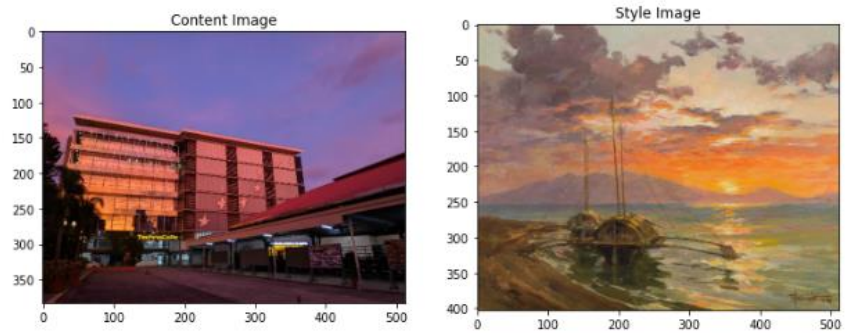
Save the image.

```
file_name = 'TIP_Ukiyo_Style.jpg'
tensor_to_image(image).save(file_name)
```

For the second art style – Fernando Amorsolo, same code were used, with just minor changes.

Step 2. Gathering data. Import the base image and the style.

```
style2 = 'FernandoAmorsolo_Style.jpg'
content = 'TIP_TechnoCore.jpg'

content_image = load_img(content)
style_image = load_img(style2)

plt.subplot(1, 2, 1)
imshow(content_image, 'Content Image')

plt.subplot(1, 2, 2)
imshow(style_image, 'Style Image')
```



Step 5. Selected VGG layers.

```
content_layers = ['block5_conv2']

style_layers = ['block1_conv1',
                'block2_conv2',
                'block3_conv3',
                'block4_conv4',
                'block5_conv4']

num_content_layers = len(content_layers)
num_style_layers = len(style_layers)
```

Step 7. Extract the Fernando Amorsolo Style and the TIP TechnoCore image.

```
class StyleContentModel(tf.keras.models.Model):
  def __init__(self, style_layers, content_layers):
    super(StyleContentModel, self).__init__()
    self.vgg = vgg_layers(style_layers + content_layers)
    self.style_layers = style_layers
    self.content_layers = content_layers
    self.num_style_layers = len(style_layers)
    self.vgg.trainable = False
```

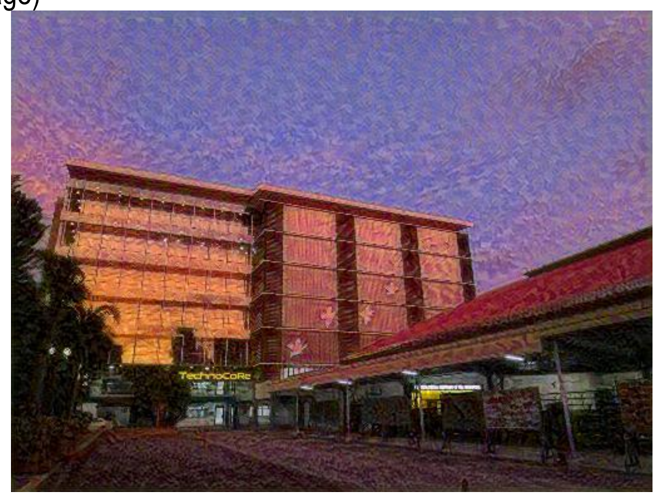
```
  def call(self, inputs):
    "Expects float input in [0,1]"
    inputs = inputs*255.0
    preprocessed_input = tf.keras.applications.vgg19.preprocess_input(inputs)
    outputs = self.vgg(preprocessed_input)
    style_outputs, content_outputs = (outputs[:self.num_style_layers],
                                      outputs[self.num_style_layers:])

    style_outputs = [gram_matrix(style_output)
                     for style_output in style_outputs]

    content_dict = {content_name: value
                    for content_name, value
                    in zip(self.content_layers, content_outputs)}

    style_dict = {style_name: value
                  for style_name, value
                  in zip(self.style_layers, style_outputs)}

    return {'content': content_dict, 'style': style_dict}

extractor = StyleContentModel(style_layers, content_layers)

results = extractor(tf.constant(content_image))

print('Styles:')
for name, output in sorted(results['style'].items()):
  print("  ", name)
  print("    shape: ", output.numpy().shape)
  print("    min: ", output.numpy().min())
  print("    max: ", output.numpy().max())
  print("    mean: ", output.numpy().mean())
  print()

print("Contents:")
for name, output in sorted(results['content'].items()):
  print("  ", name)
  print("    shape: ", output.numpy().shape)
  print("    min: ", output.numpy().min())
  print("    max: ", output.numpy().max())
  print("    mean: ", output.numpy().mean())
```

Step 8. Gradient Descent

```
style_targets = extractor(style_image)['style']
content_targets = extractor(content_image)['content']
```

Update image.

```
@tf.function()
def train_step(image):
  with tf.GradientTape() as tape:
    outputs = extractor(image)
    loss = style_content_loss(outputs)

  grad = tape.gradient(loss, image)
  opt.apply_gradients([(grad, image)])
  image.assign(clip_0_1(image))

train_step(image)
train_step(image)
train_step(image)
tensor_to_image(image)
```



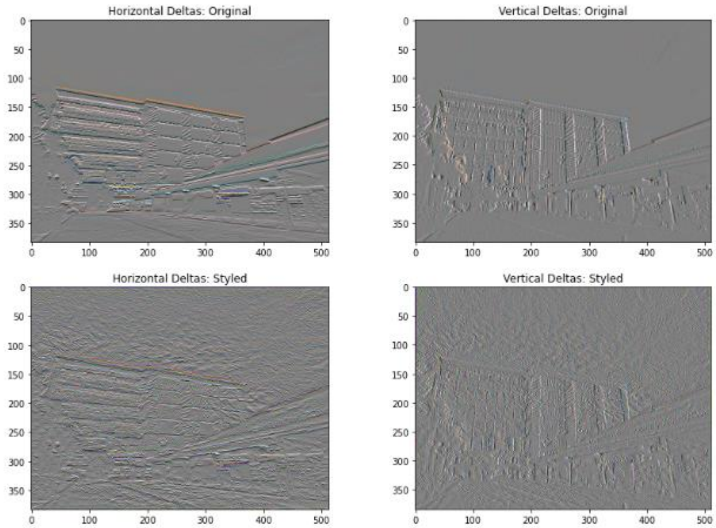
Optimize.

```
import time
start = time.time()

epochs = 10
steps_per_epoch = 10

step = 0
for n in range(epochs):
  for m in range(steps_per_epoch):
    step += 1
    train_step(image)
    print(".", end='', flush=True)
  display.clear_output(wait=True)
  display.display(tensor_to_image(image))
  print("Train step: {}".format(step))
```

```
end = time.time()
print("Total time: {:.1f}".format(end-start))
```

```
Train step: 100
Total time: 3529.8
```

```
def high_pass_x_y(image):
  x_var = image[:, :, 1:, :] - image[:, :, :-1, :]
  y_var = image[:, 1:, :, :] - image[:, :-1, :, :]

  return x_var, y_var

x_deltas, y_deltas = high_pass_x_y(content_image)

plt.figure(figsize=(14, 10))
plt.subplot(2, 2, 1)
imshow(clip_0_1(2*y_deltas+0.5), "Horizontal Deltas: Original")

plt.subplot(2, 2, 2)
imshow(clip_0_1(2*x_deltas+0.5), "Vertical Deltas: Original")

x_deltas, y_deltas = high_pass_x_y(image)

plt.subplot(2, 2, 3)
imshow(clip_0_1(2*y_deltas+0.5), "Horizontal Deltas: Styled")

plt.subplot(2, 2, 4)
imshow(clip_0_1(2*x_deltas+0.5), "Vertical Deltas: Styled")
```




```
def total_variation_loss(image):
  x_deltas, y_deltas = high_pass_x_y(image)
  return tf.reduce_sum(tf.abs(x_deltas)) + tf.reduce_sum(tf.abs(y_deltas))

total_variation_loss(image).numpy(), tf.image.total_variation(image).numpy()

total_variation_weight=30

@tf.function()
def train_step(image):
  with tf.GradientTape() as tape:
    outputs = extractor(image)
    loss = style_content_loss(outputs)
    loss += total_variation_weight*tf.image.total_variation(image)

  grad = tape.gradient(loss, image)
  opt.apply_gradients([(grad, image)])
  image.assign(clip_0_1(image))

opt = tf.keras.optimizers.Adam(learning_rate=0.02, beta_1=0.99, epsilon=1e-1)
image = tf.Variable(content_image)

import time
start = time.time()

epochs = 10
steps_per_epoch = 30

step = 0
for n in range(epochs):
  for m in range(steps_per_epoch):
    step += 1
```

```
    train_step(image)
    print(".", end='', flush=True)
  display.clear_output(wait=True)
  display.display(tensor_to_image(image))
  print("Train step: {}".format(step))

end = time.time()
print("Total time: {:.1f}".format(end-start))
```

```
Train step: 300
Total time: 9558.6
```

```
file_name = 'TIP_FernandoAmorsolo_Style.jpg'

tensor_to_image(image).save(file_name)
```

Outputs:

TIP TechnoCore – Ukiyo-e Art Style

TIP TechnoCore – Fernando Amorsolo Art Style

Discussion:

Neural Style Transfer is an algorithm technique that allows a photo and an artwork to be blended and releases an output of the photo in the style of the given artwork. For this activity, VGG19 was the chosen model to perform the neural style transfer for the TechnoCore building, the content image. The chosen art styles are from the paintings of Ukiyo-e and Fernando Amorsolo. The CNN architecture used in this activity was the deep learning model provided by TensorFlow as their tutorial.

Upon modifying the program, the proponent changed the content layer and the style layer for optimizing the blended image. For the Ukiyo-e Style, the VGG content layer was in block5_conv4. Meanwhile, for Fernando Amorsolo style, block5_conv2 was used. Both style layers were the same for the two artworks (block1_conv1, block2_conv2, block3_conv3, block4_conv4, block5_conv5). These layers were used in building the model for the optimization. Both styles undergo extractions and gradient descent before optimizing. Then, re-optimization was done for the two styles after reducing the high frequency that was obtained during the first optimization run. For the Ukiyo-e style, the epochs were set to 10, and its steps are 10 as well. Rerunning the optimization, the steps is changed to 20. For Fernando Amorsolo style, epochs remained 10, with 10 steps, and 10 epochs with 30 steps for the re-optimization.

For the results, it can be observed that neural style transfer was successfully implemented for the two styles. It only caused a huge amount of time before getting the output for the final optimization due to hardware inefficiency but was able to come up with good results.